



Computational Intelligence based EMG for Automated Classification of Foot Drop Rehabilitation

By

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Certificate of Original Authorship

I, Sahar Adil Abboud, declare that this thesis, is submitted in fulfillment of the requirements for the award of Doctorate of Philosophy in the School of Biomedical Engineering at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. IN addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

Foot drop is a complication that arises from the weakness that occurs in specific muscles in the ankle and foot; such as the Anterior Tibialis muscle (AT) during the foot flexion and extension. A lesion in the Lower Motor Neuron (LMN) will cause Foot Drop. Foot drop has been found to arise in 52% to 67% of patients with spinal Upper Motor Neuron (UMN) pathology. Foot Drop (FD) is a common disorder and is not specific to age; it affects around 1% of women and 2.8 % of men. The affected muscles impact on the motion of the ankle and foot both downward and upward. To overcome this problem and to improve rehabilitation devices, this thesis introduces several methods to improve the performance of the Myoelectric Pattern Recognition (M-PR) in both the offline and real data experiments. The thesis proposes a new M-PR system that will work satisfactorily on both the healthy and non-healthy leg by classifying movements in the offline experiments. The thesis describes the state-of-the-art procedures for M-PR and studies all the conceivable structures for the best M-PR features and classifiers.

This thesis presents new classifiers to develop the performance of the M-PR. The Self-Advised-Support Vector Machine (SA-SVM) modified from a single class to multi-class. Developments in methodology lead to more significant applications for overall use. The thesis adapted and altered label classification methods resulting in a new classification named Label Self-Advised-Support Vector Machine LSA-SVM. Further, a development to LSA-SVM is to upgrade from a single class into Multi-LSA-SVM and then to evolve the methodology to match Extreme Learning Machine (ELM) with LSA-SVM to acquire a new rapid method, named ELM-LSA-SVM. For the real data experimental option, a collected data from using the sEMG device from Foot Drop Patients in Metro Rehabilitation Hospital in Sydney, Australia using Ethical Approval (UTS HREC NO.ETH15-0152).

The collected used to apply the latest and fastest method to FD patients to use the myoelectric pattern recognition (M-PR) for leg movement detection. The experimental

results for the EMG dataset and benchmark datasets exhibit its benefits. Furthermore, the experimental results on UCI datasets indicate that ELM-LSA-SVM achieves the best performance when working together with LSA-SVM and SVM. The whole sets of experimental results are encouraging as recorded and reported in the thesis.

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I want to thank friends and colleagues who have encouraged and supported to accomplish a degree.

As a final point, I would like to acknowledge the unending love of my family who has been a constant source of support. Their faith in and encouragement has helped throughout life.

Dedication

This thesis dedicated to the five most important people in life, without their support, this journey would have been just a dream. Special thanks to mother, Sammera A.Gh., father, Adil Abboud (Allah place him in heaven), bother Jameel, Daughter Noor and my very best friends for being my inspiration and encouraging me throughout my career.

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List of Abbreviations

AFO	Ankle Foot Orthotic
ANN	Artificial Neural Network
AR	Auto-Regressive (model)
SA-SVM	Self Advised Support Vector Machine
BCI	Brain-Computer Interfaces
BPF	Band-Pass Filtering
CNS	Central Nervous System
COM	Center of Mass
CPN	Common Peroneal Nerve
CSA	Cross-Sectional Area
DOF	Degree of Freedom
DSP	Digital Signal Processor
DM	Data Mining
ECG	Electrocardiograph
eCGS	Comfortable Gait Speed
EEG	Electroencephalography
EI	Efficiency Index
EMG	Electromyography
ES	Electrical Stimulation
ESCS	Epidural Spinal Cord Stimulation
FES	Functional Electrical Stimulation
FLC	Free Fuzzy Logic Controller
GRF	Ground Reaction Force
GRNN	General Regression Neural Network
HGO	Hip Guidance Orthotics
HRF	Handle Reaction Force
IEMG	Integrated EMG
iFES-LCE	isokinetic Leg Cycle Ergometer
IOFL	Input Output Feedback Linearised
KAFO	Knee-Ankle-Foot Orthosis

KNN K Nearest Neighbour
 MA Moving Average
 macro MUP macro Motor Unit Potential
 MeCFES Myoelectrically Controlled Functional Electrical Stimulator
 MFPV Muscle Fibre Propagation Velocity
 MGH FAC Massachusetts General Hospital Functional Ambulation Classification
 MLD Multi Labelling Dimensionality
 NFES Non Function Electrical Stimulation
 NIH National Institutes of Health
 NMES Neuromuscular Electrical Stimulation
 PCI Physiological Cost Index
 PD Parkinson's Disease
 RF Rectus Femoral
 RGO Reciprocating Gait Orthotics
 RMS Root Mean Square
 ROM Range Of Motion
 RTS Randomly Timed Stimulation
 RTT Robotic Treadmill Training
 SCI Spinal Cord Injury
 SCKAFO Stance-Control Knee Ankle Foot Orthosis
 SCS Spinal Cord Stimulation
 SD Standard Deviation
 sEMG surface EMG
 SOMF Second Order Moment Function
 SThD Single Threshold detection
 TA Tibias Anterior
 TLSI Thoracolumbar Spinal Injury
 TO Toe-Off
 VL Vastus Lateralis
 VM Vastus Medialis
 VR Virtual Reality
 VSNR Virtual Signal-to-Noise Ratio
 WPT Wavelet Packet Transform
 WSTT Weight-Supported Treadmill Training.